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Human population growth offsets climate-driven increase in woody vegetation in sub-Saharan Africa

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Abstract

The rapidly growing human population in sub-Saharan Africa generates an increasing demand for agricultural land and forest products which presumably leads to deforestation. Conversely, a greening of African drylands has been reported but this has been difficult to associate with changes in woody vegetation. There is thus an incomplete understanding of how woody vegetation responds to socio-economic and environmental change. Here we used a passive microwave Earth Observation data set to document two different trends in woody cover for 1992-2011: an increase of 36% on the land area (6,870,000 km²), largely in drylands, and a decrease of 11% (2,150,000 km²), mostly in humid zones. Increases in woody cover were associated with areas of low population growth and driven by increases in CO_2 in the humid zones and by increases in precipitation in drylands, whereas decreases in woody cover were associated with areas of high population growth. The spatially distinct pattern of these opposing trends reflects (1) the natural response of vegetation to precipitation and atmospheric CO_2 and (2) deforestation in humid areas, minor in size but important for ecosystem services, such as biodiversity and carbon stocks. This nuanced picture of changes in woody cover challenges widely held views of a general and ongoing reduction of the woody vegetation in Africa.

Introduction

Africa's human population has increased from about 230 million in 1950 to over 1000 million in 2010 and is expected to grow to as high as 5700 million by the end of the 21st century[1]. This growth has led to the expansion of agricultural land and the reduction of natural forests and other woody vegetation[2,3,6], affecting biodiversity and carbon storage[3]. Severe droughts in recent decades have also had an adverse impact on humid and sub-humid forested areas[7]. In contrast, studies of drylands have shown an increase in vegetation productivity over the last 30 years[4,8], also highlighting the importance of drylands for global carbon variability and as land CO_2 sink[9]. Whether this increase in vegetation productivity is driven by the growth of woody vegetation and/or by an increase in productivity of herbaceous vegetation is not clear. This is because the scattered nature of woody plants in drylands is very different from forests with closed canopies and challenging to detect with optical satellite imagery at regional to continental scales[10,11]. Previous studies have used vegetation indices as proxies for net primary productivity, but these indices measure the photosynthetically active part of the vegetation and most studies do not distinguish between woody and herbaceous vegetation[12,13]. Furthermore, studies of deforestation in humid areas traditionally report the presence or absence of forests[3] and do not assess gradual changes in forest biomass within existing forests (e.g., forest degradation). They are also based on temporal snapshots of satellite imagery at a higher spatial resolution and only capture forests based on given definitions, e.g. tree height and canopy cover percentage[3,14], which substantially underestimate shrubs and scattered trees in drylands[10]. Consequently, little quantitative information is available about the state, rate, and drivers of change in the cover of woody vegetation at the scale of the African continent. This information is crucial for ensuring that the design of natural resource management in relation to deforestation and desertification is based on observations rather than those based on narratives.

Results

Africa's woody cover is under change

We used a new passive microwave Earth Observation (EO) data set (Vegetation Optical Depth, VOD) that captures continuous changes in the coverage of canopies of all woody phanerophytes, regardless of size, in both drylands and humid areas[15-17]. We applied VOD as a proxy for annual woody cover and documented changes in Africa's woody vegetation between 1992 and 2011, with a special focus on the changes in drylands and humid areas (defined by the ratio between annual precipitation and potential evapotranspiration, Supplementary Fig. 1a). Woody vegetation changed significantly (slope of linear regression, $p<0.05$) during 1992–2011 in approximately half of sub-Saharan Africa (47% of land areas). A majority (77%) of the significant trends were positive, covering 36% of sub-Saharan Africa and representing an overall increase of 2.1 woody cover (%) (Fig. 1a). Most (70%) of the significant positive changes were in drylands covering approximately 4 900 000 km^2 (overall change +2.9 woody cover (%)), mainly in the Sahel and southern Africa[18-20] (Fig. 2a). Positive trends are also observed in the humid zones to a much smaller extent (2 100 000 km^2), with an overall change of +0.8 woody cover (%). Negative changes affected 11% of sub-Saharan Africa, of which 75% were in humid areas (approximately 1 600 000 km^2 in humid zones and 530 000 km^2 in drylands). The decline in woody cover primarily affected areas that are also characterized by high carbon stocks (Supplementary Figs 2a, 2b), suggesting that areas with the largest carbon sinks have been disturbed at the fastest rate. The classification of woody cover change into bioclimate zones[21] confirms the overall tendency with larger increases in drier zones (except extremely hot xeric) and lower increases and decreases in moister zones (Fig. 2d).

Drivers of woody cover changes

The positive changes in woody cover in Africa's drylands are significantly related to precipitation (Fig. 1a). In contrast to herbaceous vegetation, woody plants can benefit from a higher variability and intensity of precipitation[22], as in southern Africa and the Sahel (Supplementary Fig. 1c). The dependence on precipitation was corroborated with simulations of the vegetation using the dynamic vegetation model LPJ-GUESS[23], which simulated an increase in woody biomass for 1992-2011, consistent with the satellite estimates of woody cover (Fig. 3). The relative increase of both woody cover and biomass was largest in drylands, and factorial simulations of the individual driving variables indicated that precipitation accounted for most of the simulated increase in woody biomass in drylands such as the Sahel and southern Africa (Fig. 3, Supplementary Fig. 3). Increasing concentrations of atmospheric CO_2 was a minor contributor to these dryland trends yet was the main variable driving the growth of woody vegetation in humid areas, enhancing primary production[24] (Fig. 3, Supplementary Figs. 2, 3). The absolute increase in woody biomass was largest in humid areas (mean increase of 0.04 kg C m^{-2} y^{-1} near the equator, Supplementary Fig. 2), coinciding with overall large stocks of woody biomass. Solar radiation, nitrogen deposition and temperature had minor impacts on the changes in woody biomass (Supplementary Fig. 2).

This increase in woody vegetation driven by climate and CO_2, however, was offset by anthropogenic impacts, especially in humid areas. The increase in woody cover in the VOD analysis was thus most pronounced in areas of low human population density and change (Fig. 4). Areas and countries with a higher population density and growth (Fig. 1b, Supplementary Fig. 1d) had decreases in VOD-based woody cover (Figs. 1a, 4, Supplementary Fig. 4), offsetting the climate-driven increases in other parts of the humid zones (Figs. 2c, 3). This separation in areas of high and low human pressure applied to both drylands and humid tropics. The average trend, however, remained positive in drylands, even in areas with strong population growth, but was negative in humid areas with strong population growth, regardless of the trends in precipitation and CO_2 (Fig. 2b, c). Populations increased by an average of 40 persons km^{-2} over 20 years in areas where woody cover decreased supposedly due to agricultural expansion, logging, and other uses of woody products. In contrast, populations increased by an average of only 6 persons km^{-2} in areas where woody cover increased. Human population increase was highest in moist and mesic bioclimate zones and woody cover changes were accordingly negative or low, whereas population growth was lower in xeric areas and woody cover increases were higher (Fig. 2d). At the continental scale, a simultaneous autoregressive model (SAR) explained nearly half of the spatial pattern of changes in woody cover in terms of changes in population and precipitation (r^2=0.46), with population being more important than precipitation (standardized slopes of -0.27 and 0.08, respectively) (Supplementary Table 1).

Discussion

The opposing trends in dry and humid zones have implications for our understanding of environmental change in sub-Saharan Africa. While areas of high population growth, mostly in humid zones, on average experience a decrease in woody vegetation, areas with low population growth on average experience an increase in woody vegetation, mainly driven by changes in precipitation and CO_2 concentrations. This latter increase is not captured in official forest statistics, since much of it takes place outside of humid forests.

This implies that the ‘problem’ of woody cover loss - and thus carbon stocks decreases - in the humid forest zones is at least partly balanced by an increase in drylands. ‘Bush encroachment’ in savannas of southern Africa, however, has traditionally been considered an undesired effect[14,25]. Since the VOD data used to estimate woody cover does not allow direct estimation of carbon stocks, the exact balance between gains and losses in carbon cannot be directly assessed in this study. Further work combining field measurements, ecosystem modelling and new satellite-based passive microwave sensors is required to further understand these linkages. In humid areas, woody biomass may actually increase without any change in woody cover.

The close relationship between population growth and decreased woody cover suggests that agricultural expansion, urbanization and wood fuel harvest were the main causes of the decrease in woody cover, as also found in studies of tropical deforestation[3,26]. The reduction in woody cover tends to primarily affect areas with high carbon stocks and other studies suggest that these are also areas characterized by the highest biological diversity[27]. There is, however, no simple relation between losses and gains in woody cover and biodiversity. While diversity and productivity of natural vegetation are generally positively correlated[28], this does not exclude the possibility that great losses may be experienced in areas of deforestation, while only smaller gains are seen in drylands with increasing woody cover.

Due to the impact on land surface albedo, woody cover changes in dryland areas may trigger climate feed-backs. Since the hypothesized existence of a ‘biogeophysical feed-back’[29], many studies have attempted to model such effects[30,31], with some research claiming that man-made afforestation efforts would give rise to increased precipitation[32]. The extent of the observed increase in woody cover in African drylands may impact climate if the increase continues in the coming decades, and this altered feed-back should preferably be implemented and tested in regional climate models.

Methods

VOD data and calibration to woody cover. We define woody cover as the percentage of a given area covered by woody vegetation, including both leaf and woody components (stem/branches) of woody plant canopies. The unit is woody cover (%). The VOD data was retrieved from satellite passive microwave observations quantified as brightness temperature based on the NASA-VU Land Parameter Retrieval Model (LPRM)[33]. Three passive microwave sensors, i.e. the Special Sensor Microwave Imager, the Advanced Microwave Scanning Radiometer – Earth Observing System, and the radiometer of WindSat are used to form the long-term data set by applying a trend-preserving cumulative distribution function matching without changing the inter-annual variations and long-term trends of the original retrievals[34,35]. The merged long-term VOD data set was gridded at a 0.25° spatial resolution and monthly interval from 1992 to 2011 and is consistent between different sensors[11]. VOD is sensitive to the total aboveground water content in both the photosynthetic (foliar) and non-photosynthetic (woody) components of the vegetation stratum[15,36]. Soil moisture conditions are retrieved simultaneously with the VOD information in LPRM and large variations in soil moisture can influence the accuracy of VOD, especially for dense rainforest regions. Thus VOD values exceeding 1.2 are suggested to be excluded in vegetation studies[16]. The VOD signal has been separated from soil moisture and is used as a proxy for vegetation biomass globally[34]. The VOD seasonal variation is a combined effect of the seasonal dynamics of both herbaceous (including crops) and woody vegetation[15]. We used the annual minimum VOD values as a proxy for woody vegetation cover to minimize the influence of annual herbaceous vegetation[10] and avoided values exceeding 1.2 (Supplementary Fig. 5). Areas with perennial herbaceous vegetation may lead to an over-estimation of woody cover; however, the woody cover % is usually higher in these areas concealing the influence from the herbaceous plant understory. Also, VOD data have been used to estimate forest change in South America by limiting the range of VOD values to 0.6-1.2[16]. We did not restrict the VOD range to also include young trees and shrubs, which form an important part of the community of woody vegetation. Minimum VOD agrees well with field data based on a map of woody cover for Sahel (r^2=0.80)[10] (Supplementary Fig. 5). A global map calibrated with optical high spatial resolution images and also assessing smaller trees produced similar results[37] and was thus used to transform the annual minimum VOD to the unit woody cover (%) for further analyses (r^2=0.85, slope=0.86) (Supplementary Fig. 5). A third-degree polynomial regression was used for the transformation. Woody cover <10% was predicted with an exponential regression to avoid underestimation of very low values. The VOD is insensitive to the effects of atmospheric and cloud contamination, ensuring reliable retrievals in cloudy regions e.g. central Africa.

Correlation between the trends in woody cover and changes in human population and precipitation. Precipitation data were derived from the Climate Research Unit (CRU) (data set version 3.23), which is globally available for a 0.5° grid at monthly scale and is based on the upscaling of data from rain gauges[38]. CRU precipitation data intrinsically includes some uncertainty, as the number of stations used for each grid cell varies considerably between cells and years. Even though consistency with other data sets has been shown (DINKU) and it is the most widely used precipitation data set in dynamic vegetation modelling[39], results have to be considered with caution[7]. We have tested the blended GPCP data set, without significant changes of the results, still it has to be noted that a linear trend analysis on annually summed data includes uncertainties and simplifications. We summed the monthly observations to obtain annual sums from 1992 to 2011 and resampled the data to 0.25° using a bicubic interpolation. Population data were acquired from Gridded Population of the World (GPW) v3[40], which includes estimates for 1990, 1995, 2000, 2005, and 2010, gridded with an output resolution of 2.5 arc-minutes, resampled for this study to 0.25° (nearest neighbor). GPW population data were acquired from national statistical offices and gridded based on the proportional method, which allocates population counts to grid cells based on the proportion of each administrative areal unit that overlaps the cell. The gridded counts for existing census years are then projected to the set of output years based on a simple model of population growth. The modeling was thus not based on any additional layers of data, such as land cover, avoiding potential problems of endogeneity between VOD and simulated population grids. A linear trend analysis was conducted for annual woody cover and precipitation data, and the slope multiplied with the number of years to retrieve the absolute change over time in the corresponding unit, facilitating the direct comparison with the human population data. We quantified the relationships between the changes in woody cover (estimated by VOD), population increase (GPW), and precipitation (CRU) by applying a simultaneous autoregressive model (SAR) (spatial error type[41]) to the three gridded data sets. The SAR model accounts for spatial autocorrelation and uses change in woody cover as response and log(change in population) and change in precipitation as explanatory variables. The logarithm of the human population data was applied since the relation between woody cover changes and human population is non-linear at pixel scale, i.e. if a high number of population is reached (mostly in cities), the woody cover stops to decrease further. Standardized variables were used to enable model coefficients inter-comparison (standardized variable = (variable - mean) / standard deviation).

Fires frequently occur in most African ecosystems. However, at the spatial and temporal scale of our analysis, we do not expect changes in fire regimes as a major cause of changes in woody cover in itself but rather as a consequence of human induced deforestation and land use change[42].

Dynamic ecosystem model. The dynamic ecosystem model LPJ-GUESS[23] was applied to simulate changes in woody-biomass carbon in natural vegetation for 1992-2011. LPJ-GUESS simulates the distribution of plant functional types, and each type is represented by four pools of biomass carbon: leaves, roots, sapwood, and heartwood. The latter two were added to represent the amounts of stem (wood) carbon. This variable is closely related to the woody cover estimated by VOD, but especially in tropical forests, differences are expected, as VOD is not able to fully penetrate the tree crowns[43]. Simulations were run for 1992-2011, applying monthly climate data (temperature, precipitation, sunshine duration) from meteorological stations, gridded to 0.5°×0.5° resolution (CRU TS 3.21[37]), monthly model-derived estimates for nitrogen deposition[44], and annual mean atmospheric CO_2 concentrations[45,46] based on ice-core data and atmospheric observations as forcing. Land use and land use change were not accounted for in the simulations, which were only applied to quantify the changes in natural vegetation. The simulations were preceded by a two-stage spinup: For the first stage, vegetation growth starts from bare-ground conditions, using climatic data for 1901-1930, and CO_2 levels were kept constant at the concentration for 1901. For the second stage, representing 1901-1991, the actual climate data, atmospheric CO_2 concentration and N deposition were used.

In addition to a full simulation with the forcing as described above, five factorial simulations were performed to separate the impact of individual driving variables. Only one of the four parameters (temperature, precipitation, radiation, or CO_2) was applied using the transient data as described above, whereas the other three parameters used a climatology for 1992-2011, applying monthly means over this 20-year period for the climatic parameters and an annual mean for CO_2. In the fifth factorial simulation, similar to the transient CO_2 simulation above, the changing CO_2 concentration was combined with a climatology for N deposition, to separate the impacts of atmospheric CO_2 and N deposition on the CO_2 fertilization. These simulations were applied to determine the impact of the individual driving variables on the simulated trend.

Data availability CRU precipitation data are available from the University of East Anglia (http://www.cru.uea.ac.uk/). The global tree cover map is available from the Geospatial Information Authority of Japan, Chiba University (http://www.iscgm.org/gm/ptc.html#use). VOD raster data are provided and available by Yi Liu, University of New South Wales. Gridded population maps are provided by CIESIN (http://sedac.ciesin.columbia.edu/). Humidity zones are available from http://www.grid.unep.ch/index.php.

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Author Contributions M.B., R.F., F.T. and A.V. designed the study. M.B. (VOD) and G.S. (ecosystem model) conducted the analyses with support by F.T., J.P., R.F. and J.P.. K.R. and M.B. drafted the manuscript with contributions by all authors.

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Figure legends:

Figure 1 | Changes in woody vegetation and human population over two decades. a, Significant trends of woody cover (VOD) for 1992-2011, separated by the presence or absence of a significant ($p<0.05$) pearson correlation with cumulative 2-year precipitation during this period. **b**, Changes in human populations for 1990-2010. The maps in a and b share a clear pattern, especially areas with a decrease in woody cover, and no relation to precipitation coincide with a high population pressure. **c**, SAR model of the changes between woody cover, precipitation (both 1992-2011), and population (1990-2010). The units are expressed as change in the corresponding unit over the period of analysis.

Figure 2 | Changes in woody cover (VOD) in different humidity zones. a, Areas with changes in woody cover (linear regression of change in woody cover for 1992-2011). Annual profiles of woody cover for areas of statistically significant changes in woody cover in **b**, drylands and **c**, the humid areas of sub-Saharan Africa (Supplementary Fig. 1a). Black lines characterize areas of high human population increase (>30 persons km) and grey lines areas of low human population increase (<10 persons km). **d**, Woody cover and human population changes are grouped according to bioclimatic zones21.

Figure 3 | Climatic drivers of changes in woody cover and biomass in sub-Saharan Africa. Relative trends (% of mean year-1) for 1992-2011 in woody cover (estimated with VOD) and woody biomass (simulated with LPJ-GUESS) had similar patterns of change from north to south. The trends of woody biomass were mainly driven by CO2 (humid areas) and precipitation (drylands) (Supplementary Figs. 2, 3).

Figure 4 | Links between changes in woody cover and human population. Intervals of mean population density (1990-2010, Supplementary Fig. 1d) were used to group the changes in woody cover (VOD) associated with population increases and the number of pixels showing significant woody cover change. A Chi-squared test between woody cover and population change indicated the statistically significant dependency between the two variables.

Supplementary Figure 1 | Humidity zones, changes in woody cover, trends in precipitation variability, and mean population density. a, Humidity zones showing Africa's drylands (arid, semi-arid, and dry-subhumid regions) and humid areas. These zones are based on the ratio between annual precipitation and potential evapotranspiration for 1951-1980 and were obtained from http://www.grid.unep.ch/index.php. **b,** Absolute changes in woody cover (%) (estimated from annual VOD minimum) for 1992-2011. **c,** Significant ($p<0.05$) slope of linear regression of the annual coefficient of variation (CV) of CRU precipitation for 1992-2011 showing an increasing CV in southern Africa and parts of the Sahel. **d,** Mean population density for 1990-2010.

Supplementary Figure 2 | Trends of woody biomass and their drivers. a, Mean woody cover (VOD) and **b,** Mean woody-biomass carbon (LPJ-GUESS) averaged per latitude. Differences are due to the different variables (woody cover vs total woody aboveground biomass, which differs mostly in humid forests because most woody material is stored in the stems hidden below the canopy), the saturation of VOD in the humid forests, and the poor capability of LPJ-GUESS to assess dryland shrubs, which omits large parts of southern Africa's woody vegetation. **b,** The deviation from the inter-annual mean woody biomass shows a steady temporal increase in woody biomass. **c,** The total trends of woody biomass from north to south confirm the positive trend. The relative effects of CO_2, precipitation, radiation, and temperature on the trends identify CO_2 and precipitation as the main drivers.

Supplementary Figure 3 | Drivers of simulated trends of woody biomass (LPJ-GUESS). a, b, Deviation from the mean for 1992-2011. **c, d,** Contribution of CO_2 and precipitation to the total trend. A negative value indicates an opposing trend and a positive value implies a high contribution to the total trend. CO_2 is identified as the dominant driver of the trends of woody biomass in humid areas, and precipitation is the dominant driver in drylands. Gray indicates non-significant trends.

Supplementary Figure 4 | Changes in woody cover and human population by country. Note that not only forests but all woody vegetation is captured, so these statistics are not comparable with forest losses and gains. Moreover, a change does not imply a replacement of a forest by a non-forested area.

Supplementary Figure 5 | VOD and woody cover calibration and validation. a, Raw annual VOD minimum is plotted against the woody cover map (http://www.iscgm.org/gm/ptc.html#use) which was used for transforming VOD minimum to the unit woody cover for sub-Saharan Africa. A third-degree polynomial regression was used for the transformation. Woody cover <10% was predicted with an exponential regression to avoid underestimating very low values. **b**, The predicted woody cover map (using VOD) agrees well with the global map[37] (r^2=0.85, slope=0.86) and the unit woody cover (%) was thus used throughout the manuscript. **c**, For validation purpose, VOD minimum is plotted against a field data trained woody cover map of Sahel[10]. **d**, The mean woody cover estimated with VOD minimum is shown.

Supplementary Table 1 | SAR model of the changes in woody cover. Response variable: VOD (woody-cover change, 1992-2011). Explanatory variables: log(change in population) (persons km^{-2}, 1990-2010), log(population density) (persons km^{-2}, 1990-2010), change in precipitation (mm $year^{-1}$, 1992-2011), and mean annual precipitation (mm $year^{-1}$, 1992-2011).

Supplementary Figure 6 | Flowchart of the applied data sets and methods.